Bayesian Project Diagnosis for the Construction Design Process

P.C. Matthews and A.D.M. Philip
School of Engineering and Computing Sciences,
Durham University, UK

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Abstract

This study demonstrates how subtle signals taken from the early stages within a construction process can be used to diagnose potential problems within that process. For this study, the construction process is modelled as a quasi-Markov chain. A set of six different scenarios representing various common problems (e.g. small budget, complex project) are created and simulated by suitably defining the transition probabilities between nodes in the Markov chain. A Monte Carlo approach is used to parametrise a Bayesian estimator. By observing the time taken to pass the Review Gateway (as measured by the number of hops between activity nodes), the system is able to determine with good accuracy the problem scenario that the construction process will likely suffer from.

Keywords: Markov Chains; Monte Carlo Simulation; Project Management; Design Process; Uncertainty.

1 Introduction

Building construction projects are mostly linear processes, but can iterate when faults occur. These iterations add time and cost to the construction process, especially if the iteration was not anticipated (Mitropoulos and Howell, 2002). There are several reasons for unanticipated iteration in a construction project, including poor brief, political considerations, insufficient budget, and so on. Frequently, the disruption to the project occurs later on in the execution of the project (Chester and Hendrickson, 2005). In these events, it would be beneficial to be provided with early warning that a type of problem was anticipated. If some signal could be observed early on in the process, the project manager could be made aware of the potential problem and take some suitable mitigating action.

This research seeks to exploit Bayesian methods to interpret a single signal based on the temporal progress of a project to generate diagnostic predictions of potential problems. Bayesian methods have already been used in medical contexts for supporting diagnosis, see for example Sadatsafavi et al. (2007). The Bayesian method will produce a set of probabilities that certain problems exist. This provides for an intelligent decision support system that can then be used by the project manager to interpret these in the broader context of the project execution as to what action would be appropriate. This is a significant development on previous work, such as Weidl et al. (2005); Lee et al. (2009) where multiple signals are used, which are often subjective. The diagnosis method presented in this paper aids the project manager to focus on a small number of potential problems, but does still encourage the project manager to apply expert judgement.

The remainder of this paper will first present further background to this research. This will then be synthesised into a Markov-like process model for the construction domain. This process model will then be presented with certain scenarios and the results will be analysed. Finally, there will be a discussion with regard to the model in the domain context. The paper will then conclude with comments on the approach in general.

2 Background

Process planning and scheduling are mature topics. These are essential tools that support the ability to deliver project outcomes in a timely and ordered manner. 'Modern' tools, such as PERT and critical planning, have been well studied and adopted (Kelley and Walker, 1959; Williams, 1995). While they provide the means for estimating the duration of a project and identifying that a project is off-track, they do not provide guidance as to what is causing the difficulty. As increasingly complex projects are planned with greater sources of uncertainty, these original methods require extension to be able to handle a more stochastic view of planning and scheduling.

The construction industry follows a (mostly) linear process. This process starts with the project inception and definition and is expected to terminate with the completion of the building. The process can terminate in other ways; however these represent project failures, as the project has come to some conclusion other than completing the building. Within this process there are also gateways (Soibelman et al., 2003). These gateways ensure that the project has reached sufficient maturity and quality that it may proceed to the next phase of the project. In the event that a gateway blocks the project, two outcomes are then possible: either the process must return to the start of the phase or the project is terminated (i.e. it fails).

For the purposes of this work, the Royal Institute of British Architects (RIBA) construction process is adopted (RIBA). Figure 1 contains the earliest part of that process, represented as a flowchart. This flowchart starts with the project inception and terminates at the granting of building permission. The process then continues with the construction of the building. For the purposes of this work it is sufficient to consider only the earliest phases, and will focus on the RIBA process up to and including the first gateway review (GR1).

This flowchart can be thought of as a Markov chain, as illustrated in Figure 2 (Wu and Shieh, 2006; Taha, 2007). Each element of the flowchart can be represented by a node. From each node, there are a number of nodes the process could progress on to which are represented by the directed arcs exiting the node. For example, from the 'Identify Site' node, the process could move on to any of: 'Outline Objectives', 'Determine Budget' or 'Project Definition'. This does make the assumption that projects perform only one task at a time; however, for the purpose of this research, this is not critical. When simulating the design process, the node that the process moves on to is determined stochastically. Specifically, each arc has a predetermined probability of being followed. Based on these probabilities, an arc is selected at random, thereby moving the process on to the next step. For the simulation model, these probabilities were estimated through a combination of literature and discussions with domain experts.

2.1 Construction Design Process

The construction design process is a variant of generic product development, as described by for example Pahl and Beitz (1996) and Cross (2000). The fundamental aspects of this process are that is mostly linear, but divided into major sections (phases) which are delimited by stage gates (Cooper et al., 2002; Soibelman et al., 2003). These stage gates provide the opportunity to review the progress of the project and determine if it should go ahead, require further work within the current stage or be terminated. This ensures that 'weak' designs are not taken through to further downstream phases thereby wasting resource or risking failure (Von Stamm, 2008).

The construction industry is varied, ranging from building construction through to highway laying. This work will focus on building construction, due to its generality: individual building professionals (architects, builders) will tend to specialise in certain types of buildings due to the level of specialist knowledge that is required. However, there remains common ground across all these specialist domains. Firstly, the design stage is common across all domains. The client proposes an idea for a building project and it is then up to the architect to transform this idea into a practicable building solution. To achieve this successfully, the design must satisfy the client's requirement for both the functionality and aesthetics of the building. Secondly, the financial considerations of a building project are common. Typically there is a fixed overall budget with very little leeway for the total cost. The client will have expectations of what can be achieved for the budget and it is the architect's responsibility to provide solutions that can maximise what can be achieved for that budget. Thirdly, the consideration and adherence to legal issues is common. There are significant numbers of legal regulations that buildings must adhere to. Although there will be different specialised legislation for different types of building projects, the overall process of adhering to legislation remains common.

In the UK, the building process is governed by a set of rules detailed by RIBA. These rules divide the construction process into several stages. The main stages are defined as: (1) Preparation, (2) Design, (3) Pre-construction, (4) Construction, and (5) Use. Each main stage is then further broken down into smaller work stages. This work will focus on the first two of the RIBA main stages: Preparation and Design. These stages occur before significant resource has been invested into the project, and therefore it is during these stages where it is easiest (most cost-effective) to change the design. The reasons for changing design could be for any number of reasons, including misinterpretation of the brief, change in budget, or change of opinion.

Clough et al. (2000) note that the 'Planning and Definition' stages of the project must define the requirements and (budgetary) constraints. The project definition must include "establishing broad project characteristics such as location, performance criteria, layout, equipment, services and other owner requirements needed to establish the general aspect of the project". The design phase involves completing the architectural and engineering design of the entire project. This results in the production of the final working drawings and specification of the total construction programme.

Ritz (1994) states that the most critical stages of the pre-construction phase is planning for construction execution and resource useage (time, money, equipment). In projects where these aspects are neglected, there is a greater risk in the project of failure at a later stage due to overruns of time and/or money.

Any significant construction project will have a number of independent parties involved. Therefore a key factor in the success of a construction project lies within the communication between these parties (Chan et al., 2004). Specifically, it is the quality of the communication at certain key points within the process that has a significant impact on the outcome of the project (Emmitt and Gorse, 2003). These key points are characterised by a decision that has to be made which would be extremely difficult to change once the decision has been implemented. Lack of communication may result in changes having to be made, and these changes can result in negative consequences. An example of poor communication occurs in deciding the shape and floor plan of a building: if the appropriate parties are not made aware of this decision, there are several significant downstream design aspects that are affected, with potentially damaging results.

The challenges listed above give rise to the potential difficult scenarios a construction process can find itself in. These are further detailed in Table 1.

2.2 Uncertainty within Construction

Construction projects frequently overrun, measured in terms of either time or financial resources (Flyvbjerg et al., 2002). Given that the budgets are set before any (physical) work is done, this is perhaps not too surprising. Essentially, the early phases of the construction process formulate an executive plan of work. The resources required for the various tasks involved are based on estimates and assumptions of how well the work will progress. These estimates and assumptions form the first source of uncertainty.

The construction process is complex, and contains a number of actors (e.g. client, architect, builder, planners, etc.). Although the interaction between these actors is defined in terms of when they should occur and how they should proceed, there is no guarantee that this will happen. Further, the quality of the interaction is determined by the abilities of each actor. Ineffective or poor actions taken by certain actors will generate unacceptable work or fail to meet predetermined deadlines. Unacceptable work will require rework, which in turn will cause delays (Mitropoulos and Howell, 2002). These events occur seemingly randomly (although will be biased by the capabilities of the various actors), and hence represent the second source of uncertainty.

Finally, the construction process occurs outdoors. In this context there are external events that are beyond the control of any of the actors within the construction process, such as extreme weather. This introduces the third and final source of uncertainty.

2.3 Project Monitoring and Risk Management

There have been a number of attempts at modelling the construction process stochastically (as well as other processes, such as the software engineering process). There are two levels at which these models operate: the first is to simply simulate the process under certain conditions and the second is to diagnose the process based on certain observations. Both these approaches require an understanding of the sources of uncertainty and the structural relationships between the various tasks within the processes.

The first level of model focused on process simulation. Chapman (1990) is one of the earliest to use the term 'risk engineering'. This is applied to an offshore pipeline laying project that consists of five key tasks. The duration of each of these tasks is represented by a probability distribution along with the number of days that are workable each month of the year. The simulation model's output provides a clearer picture of the overall project risks given these conditions, which are then in turn used to decide when and how best to proceed with the pipe laying project. Fenton et al. (2002) and Khodakarami et al. (2007) use Bayesian Belief Networks to model and simulate the software engineering process. In Fenton et al. (2002), the simulation is used to estimate the number of software defects that exist in complex software packages based on a number of project characteristics, such as level of project complexity and development process maturity. This simulation provides a distribution of the possible number of faults, and enables a project manager to compare various options for shaping the project. A similar simulation approach is taken in Khodakarami et al. (2007) to estimate the total software engineering process duration. Neil et al. (2005) use a Bayesian Network to assess financial institutions' exposure to rare but significant risk based on simulations using some basic stochastic estimates on frequency of extreme events and severity of extreme events. Moving to the construction process domain, Anderson et al. (2009) simulate the construction process as a planning and constraint satisfaction problem with stochastic task durations. This supports different scenarios being simulated by modifying the probabilities that certain events will occur, which in turn have an impact on the total project duration. This enables a project manager to better plan for contingencies due to potential predictable events occurring. Nasir et al. (2003) identify a set of schedule affected risks and construct a Bayesian Belief Network (BBN) based on these risks. Assuming a project manager knows which risks are occurring, this can then be used by a Monte Carlo simulation to compute a revised project duration estimate. Kim and Reinschmidt (2009) adopt a similar approach, but use the percentage of project completion as an input to estimate the overall completion date. Finally, Cho and Eppinger (2005) use Design Structure Matrices, an approach that is similar to Markov chains, to re-arrange task orders to minimise the effect of iterations within the design process.

The second level of model seeks to diagnose a given process. McCabe et al. (1998) describe an early attempt to use Bayesian Belief Networks to diagnose a construction process by observing queue lengths for various construction services related to a project. In the software engineering domain, Fan and Yu (2004) use a Bayesian Belief Network to infer the risk level for a given software project based on observations such as developer experience, time pressures, etc. The result is used to determine if the project has an appropriate level of resource allocated to it. Lee et al. (2009) use a Bayesian Belief Network to identify potential risk sources in a running project based on observed risk level of a set of 26 identified risk categories. Through partial observation or estimation of some of these risks within a project, it is possible to identify which are the driving risk factors in the project and therefore support the management of these risks by the project manager. Weidl et al. (2005) constructs a Bayesian Belief Network to monitor a large continuous process. This is again based on observed variables which are fed into the BBN. The BBN then presents a ranked set of potential root causes for any potential problems by identifying the variables that are driving the system into a problem state. Dissanayake and Robinson Fayek (2008) provide a project diagnosis tool based on fuzzy logic that is capable of identifying what might be affecting a particular task within a larger construction project. It is therefore clear that Bayesian methods can successfully help diagnose projects. Given the stochastic nature of Markov chains, it is plausible that Bayesian methods can be used to help analyse how an unknown Markov process has been parameterised based only on observing it move through its states.

2.4 Conclusion

The general construction process can be reasonably modelled as a Markov chain, with probabilistic transitions from one activity to the next. Although for any specific project there will have been deterministic reasons for moving from one activity to the next, this is not important when considering a large set of projects which will appear to randomly move the process. Further, given that the exact nature of uncertainty in a *current* project is unknown, the best estimate that can be made for the transition probabilities at the outset are given by prior probabilities. Specifically, when thinking about the future possible directions for a project that is about to start, a stochastic approach is suitable. As further information is gathered, this can be used to refine the understanding of the nature of project under execution.

3 Process Modelling Methodology

The process modelling methodology is based on a Markov chain (Pandelis, 2010; Eckert et al., 2004; Flanagan et al., 2007). A Markov chain consists of a set of nodes which are linked by directed arcs. The temporal domain is modelled discretely, namely that one action happens per discrete time step. The nodes represent activities and the arcs then represent the possible subsequent nodes the process could move to in the next time step, potentially including a 'loop-back' arc, which models the process remaining in the same state at the next time step.

One aim of this work has been to make this approach broadly applicable within the construction industry. In order to achieve this, the key generic process stages in the early construction process were identified, based upon the authoratative RIBA framework. These stages are represented as the nodes in the Markov chain (Figure 1). The nodes are:

A Project inception and definition: the 'official' start of the project; formulating the core ideas of the project

B Identify site: selection of the project location

C Outline project objectives: specification of the fundamental design ideas

D Determine budget: identify the total funding for the project

E Appoint design team and Project Manager: identify the team of individuals who will execute the construction project

F Outline project programme and risks: define the various stages within the construction project, and associated expected time and cost

G Develop ideas and preliminary sketches: creating the first designs, including architectural drawings

H First stage planning 'outline approval': informal discussions with local planning authorities and regulatory committees to gauge opinion and ensure there are no fundamental reasons why the project cannot proceed

I Prepare project master programme and procurement strategy: update the original programme and agree; draw up the bill of quantities

J Perform feasibility study/site investigation: all site investigations are performed

K Complete preliminary design and Construction Design and Management review: any changes to the design are made, and the programme is checked for Health & Safety conformity

L Confirm final brief: all changes are agreed and the designs are finalised

M Detailed design specifications and technical drawings: Produce the technical drawings in full detail

N Finalise costs: agree the overall budget, including any changes from original budget

O Finalise project programme: agree the overall timeframe for the construction work

P Apply for Planning Permission: ensure that all aspects of the project adhere to the rules dictated by the authorities and apply for planning permission

At the outset of a project, it is assumed that none of these tasks have been started. Each node contains a completion status, and hence at the outset of the project these are all set to 'false' (incomplete). This is proposed as a 'quasi-Markov' chain in the sense that it is an extension to the pure Markov chain, which is memoryless. The addition of 'node-memory' through a status variable provides a more intuitive model for the construction process where a number of tasks can happen in parallel and must all have been completed successfully. Therefore, the node status can be used at various stage gates to ensure that all relevant tasks have been completed and that the project may proceed. To implement this, it was also necessary to develop 'gateway' nodes that were able to verify the completion status of prior nodes. In a Markov chain process, the simulation can only be at one node (task) at any point in time. Therefore, the Markov chain is not able to represent a process with concurrent tasks. While this is not a realistic representation of a real construction process where tasks do happen concurrently, this limitation does not significantly affect the overall result, which is the time taken, as measured by number of steps taken, for the process to complete. The gateway nodes were inserted at key stages within the construction process. The key stages are where there is a significant transition in the project. Within the RIBA framework, this occurs when moving into and out of RIBA Stage C, and is labelled GR1 in Figure 1. This gateway represents a review of the project status, and if the project is not in a satisfactory state it sends the project back to the start. The transitions from the gateway node are again modelled stochastically, however should the gateway review fail the process returns to the earlier state with status aspects intact (for example the site will remain identified). The result of this is that a different set of transition probabilities come into effect. This different set of transition probabilities represents the fact that some work has been done on the project and this will impact how the process is likely to flow through the nodes second time around. In particular, it assumes that the whole project does not restart. That outcome would be modelled by a failure. The transition probability tables can be found in the appendix.

In addition to the activity nodes, it is also necessary to include terminal nodes. These are nodes that from a Markov simulation perspective can be entered but can never be left. When the simulation process enters one of these nodes, that simulation run terminates. For this simulation, there are two types of terminal nodes: success and failure. The success terminal node is entered when all tasks in the construction process have been successfully completed and in this case represents that planning permission has been granted. Upon granting planning permission, the construction project is able to proceed with the physical construction. The failure nodes represent where the project is cancelled. There are a number of points within the construction process where it is possible to cancel the project, and hence there are a number of different failure terminal nodes. It is assumed that once a project enters a failure node, there is no possible remedial action to be taken and that therefore the project is completely abandoned. It is also theoretically possible due to the cycles that exist in the Markov chain that a process can take an arbitrary number of hops to reach a terminal node. Therefore to ensure that a simulation run terminates, the Markov simulation is terminated after 60 steps and is deemed to have failed. It should be noted that very few simulations result in this outcome.

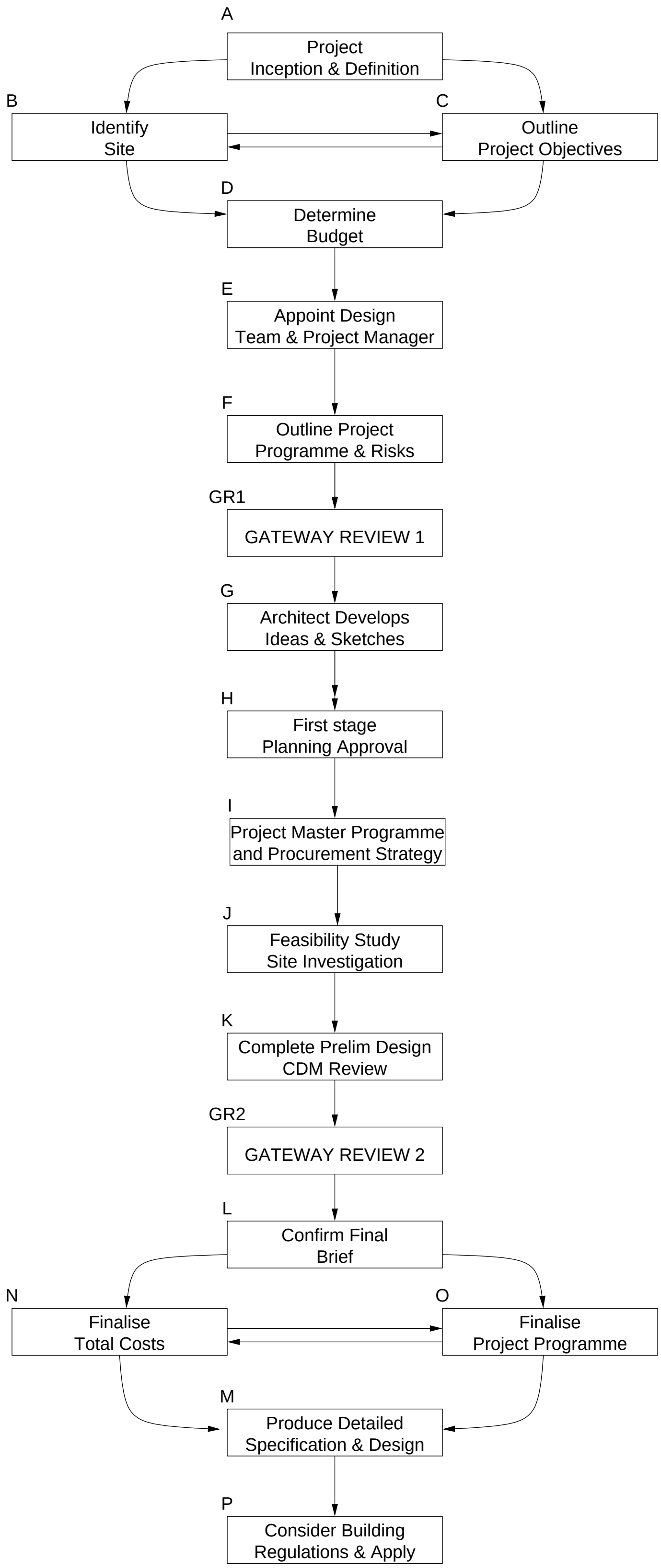


Figure 1: Overview of the full early phases of the RIBA process.

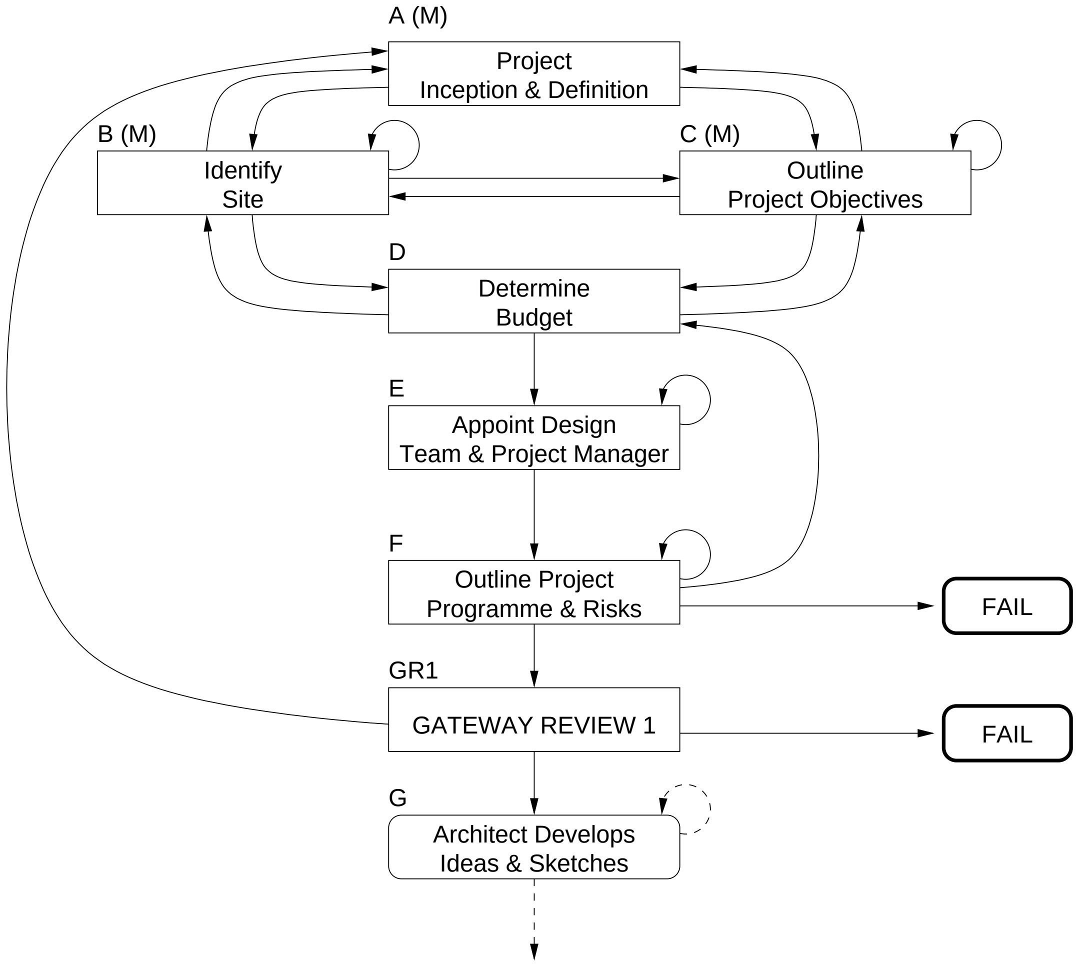


Figure 2: Detailed view of the quasi-Markov chain implementation of the RIBA process for this study. Legend: (M) indicates a state with memory, Rounded boxes represent terminal nodes, dashed arcs are not included in the Markov chain.

Once the nodes have been determined, the next step is to connect the nodes with directed arcs. The ‘normal’ progression of the project, as determined by literature (e.g. RIBA), is straightforward to implement. These arcs determine how the project would progress if all went well: all activities are successful and there is no need for any rework. However, for a complete simulation framework, it is also necessary to represent how the process progresses when activities are not successful. This is modelled by arcs linking a node to a ‘previous’ node, or possibly as a loop-back to the original node. It is worth noting that feedback loops do not feedback any further than the gateway ‘above’ them. This is as it is assumed that once the project has passed a gateway, all the tasks prior to that gateway have been successfully completed and therefore do not need revisiting.

3.1 Parametrisation of the Markov chain transition probabilities

The construction process simulation model is a subset of the first six activities of the RIBA process (Figure 2), beginning with ‘Project Inception and Definition’ through to ‘Outline Project Programme’, and contains a set of activity nodes and arcs connecting these nodes. In this case, each node is connected to between two and five other nodes. These connections represent the possible outcomes from each activity node. The parametrisation of the model is the association of a probability distribution for each node that represents the transition probabilities for following each arc. These probability values determine how the simulation proceeds through the construction process model (Taha, 2007). Therefore, it is important that the probability values are as realistic as possible. Specifically, if the probability of a task being successfully completed is too high, then the simulation will register that is takes fewer attempts to achieve this task than is reality. Conversely, setting a probability too low that a task would be completed will result in the simulation reporting that the overall process time is higher than in reality.

The estimates for the probability values in this work were arrived at through expert estimation. A three member panel of experts consisting of a construction project manager (employed by a university undertaking a significant building project), an architect from a large construction firm, and an independent academic with an expertise in civil engineering and a background in planning. Using the RIBA process, the experts placed coarse estimates for each activity as to how frequently they either moved onto a next stage or that they required more effort at that stage. They also estimated how frequently they had moved erroneously (i.e. that they would have to revisit that activity at a later time). This estimation process was first undertaken for the ‘Nominal’ scenario (where no significant negative influences exist). Using the Nominal scenario probabilities, the probability transition tables were estimated for the remaining scenarios. These other scenarios represent departures from the Nominal scenario, and using the scenario characteristics in Table 1, revised transition probabilities were estimated. This is expanded on in the following section.

3.2 Scenario development

The primary aim of this work is to seek warning signals given by construction projects that are at risk of performing poorly. A signal is defined as an observation that could be linked to a potential future problem. Observing these signals will provide the opportunity to take preventative action to ensure that the problem does not impact the project in the future. The signals that will be observed in this work are temporal: specifically how long the project takes to enter certain nodes. For example, consider the following scenario: a construction project has progressed to the point where it had detailed the building material and identified the source for the material. However, due to unforseen circumstances, the preferred building material supply company goes out of business. The builder must now identify a new preferred supplier and potentially review the design if certain requested materials are no longer available. This adds to the time it takes the project to progress to the next gateway review, and it is this longer than expected time that is observed as the signal.

To be able study these signals, it is necessary to also parameterise models for construction processes where problems occur. By simulating the various scenarios using the different models, it will be possible to analyse the characteristics and develop methods for identifying if a construction process is at risk of being in trouble.

The basic scenario that is considered is where all tasks have nominal, or 'good', transition probabilities. This represents a realistic ideal case, where there might be some rework necessary, however this is not the result of some fundamental problem within the project. In addition to this nominal scenario, a set of common problems were identified and used as a basis for developing problematic scenarios. Table 1 details a set of problematic scenarios with their associated design issues and main affected process nodes.

For each scenario the nominal transition probability table was modified to represent the changes in how the process would proceed. It should be noted that only the transition probabilities were modified, not the structure of the Markov model. By considering for each scenario which nodes were affected, the relevant feedback arcs had their associated probabilities increased at the expense of the probabilities of the forward progressing arcs. This represents that for these nodes there was a greater chance that the project would either remain at that node for longer (increasing the probability of the loopback arc) or be more likely to return to an earlier node due to the need for further rework (increasing the probability of a feedback arc). The complete transition probability tables are included in the Appendix.

4 Bayesian based Scenario Identification

The premise of using the process model as a means of identifying what potential scenario is being played out is based on Bayesian theory. Using the signal of how long (in terms of number of hops) it takes from the start of the project to pass the first gateway and denote this λ. Then by using Bayes, it is then possible to compute the probability for being in each scenario (S_i) given this signal (Pearl, 2000):

$$P(S_i|\lambda) = \frac{P(\lambda|S_i)P(S_i)}{\sum_j P(\lambda|S_j)P(S_j)} \tag{1}$$

This equation can then be used to determine the most likely scenario once the signal (λ) has been observed. The conditional probability $P(S_i|\lambda)$ is computed for all possible scenarios $S_1, S_2, \ldots, S_N$. These scenarios can then be ranked according to their associated conditional probability score. This ranked list can then be used by a decision maker, for example the project manager, to further investigate the root cause of any difficulties. Typically, the project manager would only need to consider the top two scenarios. Depending on this person's experience, the manager would either be able to further investigate along the lines of causes (in the case of a novice) or be able initiate suitable mitigating efforts directly (in the case of an expert). In either case, as the project manager is being presented with a ranked list, this removes any initial prejudice.

To be able to successfully use Bayes' theory, as expressed in Equation 1, there is also a need for further probabilistic information. Specifically, there is the need to know the prior probability of each scenario, $P(S_i)$, and the conditional probability distribution of λ for each scenario, $P(\lambda|S_i)$. The method for obtaining this information is detailed in the following sections.

4.1 Scenario Prior Probabilities

The scenario prior probabilities, $P(S_i)$, represent the probability that any given scenario occurs. A simple means for obtaining this probability is to consider the history of construction processes and measure the proportion that each scenario occurs within this history. For example, 35% of all projects suffer from having a poor brief, then $P(S_{\mathrm{PB}}) = 0.35$.

In practise these scenario priors would be different for every different project manager, or construction company. It effectively measures the different abilities of an individual contractor to fall into the various scenarios. The 'better' the contractor, the greater the probability that the 'standard' scenario occurs. Specifically, a poor contractor will have greater uncertainty as to how a project will unfold. This will be reflected in higher probabilities for the various scenarios at the expense of the probability of the nominal scenario. Conversely, a highly experienced and

Table 1: Problematic Construction Process Scenarios

Scenario	Design Issues Caused	Main Affected Nodes
Over Complex Design	Underground conditions may be an issue; Regulation needs are more complex; Unrealistic time demands; Poor management due to complexity; Project complexity is increased	Determine Potential Budget; Prepare Project Master Programme; Perform Feasibility Study; Finalise Project Programme; Produce Detailed Design
Small Budget	Supplier problems; Client requirements increase; Cost cutting reduces quality; Under estimating costs; Poor management: attempting to achieve results with insufficient resource	Determine Potential Budget; Prepare Project Master Programme; Total Costs Finalised
Difficult Planning Approval	Political considerations make progress more difficult; Increasing Health & Safety needs; Regulatory requirements increase complexity of tasks; Disputes may cause delays	First Stage "Outline" Approval; Produce Detailed Design; Consider Building Regulations
Poor Brief	Client requirement changes; Brief continuously being modified; Poor client visualisation due to lack of clarity; Errors by the construction team; Designer decisions that the client does not like	Outline Project Objectives; Architect Develops Ideas; Complete Preliminary Design Review; Confirm Brief – Final; Produce Detailed Design Spec
Tight Schedule	Unrealistic time demands; Mistakes due to rushed work; Poor workmanship; Poor management	Outline Project Programme; Finalise Project Programma; Prepare Master Programme; Total Costs Finalised

Table 2: Scenario prior probabilities.

Scenario (S_i)	$P(S_i)$
Nominal	0.15
Complex	0.10
Small Budget	0.10
Difficult Planners	0.05
Poor Brief	0.35
Tight Schedule	0.25

successful contractor will be able to better define and resource the project from the outset which will result in a very high probability for the nominal scenario.

Similar to the transition probabilities, these prior probabilities were also obtained from the expert panel. However, they were able to consult project histories to obtain a more objective estimate. The prior probabilities used here are listed in Table 2.

4.2 Model Calibration

The calibration of the model is in effect determining the conditional distribution functions for λ, i.e. $P(\lambda|S_i)$ for each possible scenario. It is assumed that the underlying model for this conditional distribution is either a Poisson distribution or a Normal distribution. This is reasonable: the Poisson distribution models the time taken for an event to occur and is parametrised by a single value representing the expected duration, whereas the Normal distribution is a good distribution where averages are taken over larger event samples. For quasi-Markov chain, it can be thought that successfully passing a gateway is in effect waiting for an event to occur and hence suitable for being represented by a Poisson distribution. However, due to the potential of having several cycles in the quasi-Markov process, this represents a more general category and the frequency distribution here might be better represented by the Normal distribution. The Poisson distribution is defined by a single parameter λ and is given by f_P (Kreyszig, 1999, p. 1081):

$$f_P(x; \lambda) = \frac{\lambda^x e^{-\lambda}}{x!} \tag{2}$$

The Poisson distribution has the property that the mean and standard deviation of the distribution are both equal to the parameter λ. This λ represents the mean number of 'hops' that the process would take to pass the gateway.

The Normal distribution is defined by two parameters, μ and σ^2 and is given by f_N (Kreyszig, 1999, p. 1085):

$$f_N(x; \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{3}$$

The Normal distribution as defined above will have a mean value of μ and a variance given by σ^2. Similar to the Poisson distribution, μ would be the average number of hops taken to pass the gateway. However, there is the additional degree of freedom to independently set the variance.

As described in Section 3.2, every scenario has an associated set of transition probabilities for the quasi-Markov chain. Therefore, to calibrate a scenario's conditional distribution, a Monte Carlo approach was adopted. The Monte Carlo approach runs the quasi-Markov chain several times to generate an observed distribution of time elapsed (measured in 'hops') to pass the first gateway node. Both the Poisson and Normal distributions are then fitted against this empirically generated distribution. If $f_O(x_i)$ is the observed frequency of what proportion of simulations that passed through the gateway at time x_i, then the Poisson parameter λ can be estimated by taking the mean of the observed sample. Similarly, the best fit for the Normal distribution will be given by estimating the μ and σ^2 parameters with the observered sample mean and variances. A χ^2 test is then used to measure which of the two models fits the observed data best. The χ^2 test for the Poisson distribution is given by (Kreyszig, 1999, p. 1138):

$$\chi_P^2 = \sum_i \frac{(f_O(x_i) - f_P(x_i;\lambda))^2}{f_P(x_i;\lambda)} \tag{4}$$

A similar expression is used for computing the χ_N^2 statistic for the quality of fit against the Normal distribution. The model with the smallest χ^2 statistic value is then selected to represent the distribution for that observed scenario. This process must be performed for every scenario. The results are listed in Table 3 and illustrated graphically in Figure 3. These results represent the calibrated signal models for each scenario. So for example, for the Nominal case, the value of Poisson χ^2 test (1.50) is smaller than that of the Normal χ^2 test (7050, see first row of Table 3), and so the distribution of time taken in the Nominal scenario is modelled by a Poisson distribution. When a signal is observed in a future process, these models are then used to determine the probability that the signal would have resulted from each scenario.

4.3 Application of Model

Using Equation 1 with the appropriate probability distribution, the model computes which scenario is most likely to be occurring based on the single observed value of how long it takes to pass the first gateway, denoted by λ. This is done for each scenario, each time using the appropriately parametrised scenario model. As there is only one observed value, λ, it is possible to generate a lookup table for a range of values of λ and then rank the possible scenarios. Table 4 lists the probabilities for each scenario given a λ value. These have been given to 6 decimal places, as there are values of λ where the probabilities are very close.

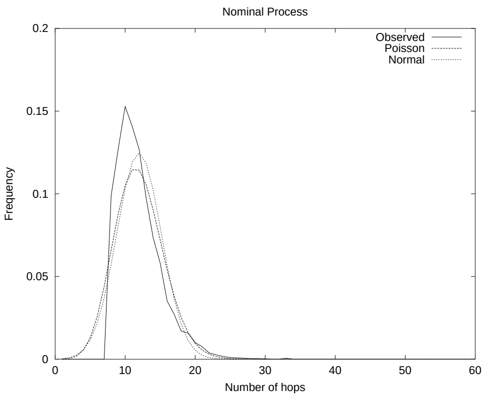
Table 5 is the equivalent table but presented by rank order. These lookup tables can then be used by the project manager as a guide for diagnosing a construction process based on the time taken to pass the first gateway node. The project manager is then able to use this information to determine if any mitigating action should be taken to minimise any potential downstream process affects.

5 Illustration

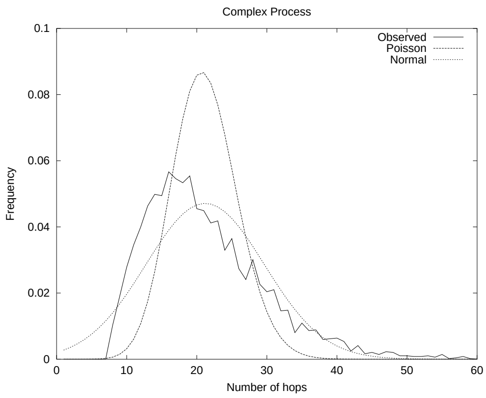
To demonstrate how the project diagnosis system is used, two illustrations are given. These are based on fictitious cases, primarily focusing on how long the construction process takes to pass the first gateway review node. The first illustration is a case where the project has swiftly moved through the first gateway. The second illustration is a case where there have been more delays and the process has taken longer to pass through the first gateway. In both cases, the project

Table 3: Model calibration results: Scenario model parameter estimates based on simulation data: $\hat{\lambda}$ (mean number of hops), variance ($\hat{\sigma}^2$) along with χ^2 test statistics for Poisson and Normal models.

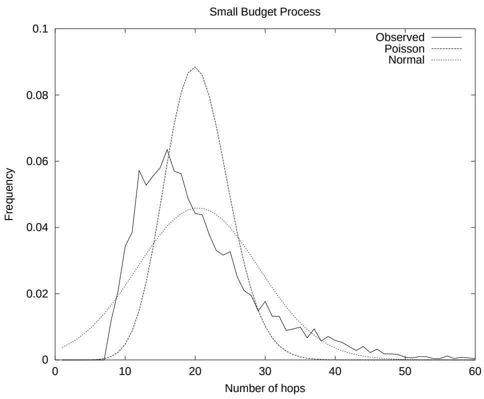
Scenario (S_i)	$\hat{\lambda}_i$	$\hat{\sigma}_i^2$	χ_P^2	χ_N^2	Model
Nominal	11.98	10.23	1.50	7050	Poisson
Complex	21.19	71.73	4.51×10^4	0.57	Normal
Small Budget	20.41	75.50	6.25×10^5	0.91	Normal
Difficult Planners	15.10	33.69	6.13×10^5	384	Normal
Poor Brief	16.81	41.54	5.10×10^8	12100	Normal
Tight Schedule	18.41	75.92	1.70×10^7	2.0	Normal



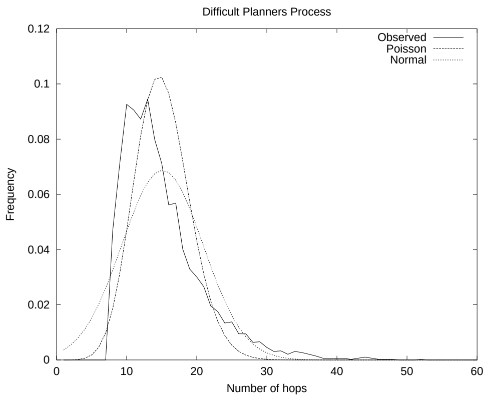
(a) Nominal



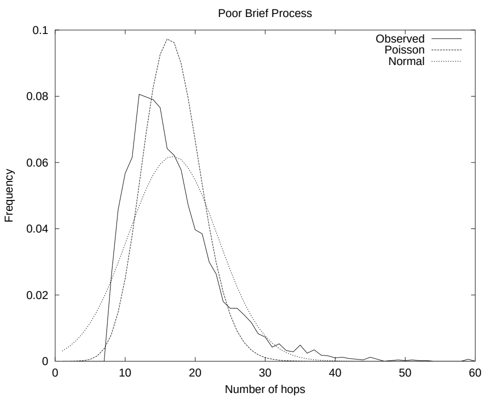
(b) Complex



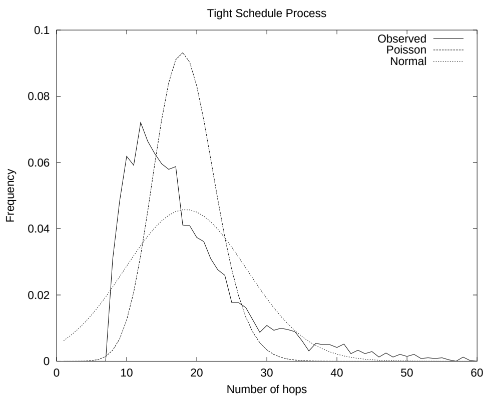
(c) Small Budget



(d) Difficult Planners



(e) Poor Brief



(f) Tight Schedule

Figure 3: Calibration of the model: for each scenario, the simulation data is plotted along with the best estimate for the Poisson and Normal distributions.

Table 4: Posterior probabilities for all scenarios for $8 \leq \lambda \leq 32$ (6 d.p. is used to illustrate ranking in cases with near equal probabilities).

λ	Nominal	Complex	Sm. Budget	Diff. Planners	Poor Brief	Tight Sch.
8	0.344521	0.048824	0.057724	0.056648	0.296987	0.195296
9	0.370304	0.047042	0.054561	0.055632	0.292808	0.179653
10	0.376371	0.046963	0.053471	0.055725	0.296104	0.171366
11	0.364707	0.048489	0.054234	0.056825	0.306561	0.169184
12	0.337966	0.051505	0.056632	0.058686	0.323238	0.171973
13	0.299431	0.055882	0.060445	0.060939	0.344613	0.178690
14	0.253144	0.061442	0.065423	0.063124	0.368568	0.188299
15	0.203746	0.067954	0.071280	0.064747	0.392521	0.199752
16	0.155892	0.075155	0.077713	0.065373	0.413807	0.212059
17	0.113400	0.082799	0.084460	0.064724	0.430188	0.224430
18	0.078563	0.090715	0.091346	0.062731	0.440257	0.236388
19	0.051997	0.098836	0.098315	0.059517	0.443543	0.247792
20	0.033000	0.107191	0.105403	0.055331	0.440322	0.258753
21	0.020160	0.115866	0.112706	0.050469	0.431286	0.269512
22	0.011895	0.124971	0.120336	0.045216	0.417262	0.280320
23	0.006797	0.134594	0.128384	0.039819	0.399044	0.291361
24	0.003770	0.144790	0.136907	0.034479	0.377336	0.302718
25	0.002033	0.155564	0.145914	0.029352	0.352771	0.314366
26	0.001068	0.166868	0.155371	0.024557	0.325953	0.326184
27	0.000546	0.178608	0.165197	0.020181	0.297493	0.337974
28	0.000272	0.190643	0.175280	0.016280	0.268036	0.349488
29	0.000133	0.202802	0.185479	0.012885	0.238253	0.360450
30	0.000063	0.214891	0.195639	0.009999	0.208824	0.370585
31	0.000029	0.226715	0.205604	0.007605	0.180401	0.379646
32	0.000013	0.238088	0.215232	0.005668	0.153565	0.387435

Table 5: Scenario ranking from posteriors for $8 \leq \lambda \leq 32$.

λ	Nominal	Complex	Sm. Budget	Diff. Planners	Poor Brief	Tight Sch.
8	1	6	4	5	2	3
9	1	6	5	4	2	3
10	1	6	5	4	2	3
11	1	6	5	4	2	3
12	1	6	5	4	2	3
13	2	6	5	4	1	3
14	2	6	4	5	1	3
15	2	5	4	6	1	3
16	3	5	4	6	1	2
17	3	5	4	6	1	2
18	5	4	3	6	1	2
19	6	3	4	5	1	2
20	6	3	4	5	1	2
21	6	3	4	5	1	2
22	6	3	4	5	1	2
23	6	3	4	5	1	2
24	6	3	4	5	1	2
25	6	3	4	5	1	2
26	6	3	4	5	2	1
27	6	3	4	5	2	1
28	6	3	4	5	2	1
29	6	3	4	5	2	1
30	6	2	4	5	3	1
31	6	2	3	5	4	1
32	6	2	3	5	4	1

Table 6: Ranked list of predicted scenarios for the case $\lambda = 11$ and associated conditional probabilities (to 2 d.p.).

Rank	Scenario (i)	$P(S_i \vert \lambda = 11)$
1	Nominal	0.36
2	Poor Brief	0.31
3	Tight Schedule	0.17
4	Planning	0.06
5	Small Budget	0.05
6	Complex Project	0.05

manager is unsure if there are underlying problems and if so what they might be. In each case, the aim is to illustrate how the system can be used to provide a ranked list of potential problem sources to the project manager. It then remains to the project manager to decide how to use this information.

5.1 Nominal Scenario

In the first scenario, the construction process progresses swiftly through to the first gateway. Specifically, in this scenario it is observed that the process passes the first gateway review after 11 'hops', i.e. that in this case $\lambda = 11$. From Table 5, the ranked order of the potential scenarios can be read (namely, 1 Nominal, 2 Poor Brief, 3 Tight Schedule, 4 Difficult Planners, 5 Small Budget, and 6 Complex Project). Table 6 expands on this by including the conditional probabilities for each scenario. It should be noted that Table 6 is simply the ranked set of probabilities taken from the row $\lambda = 11$ from Table 4.

From Table 6 the project manager can determine that this project is most likely running without any significant problems (the Nominal case) due to $P(S_{\mathrm{N}}|\lambda = 11) = 0.364707$ having clearly the greatest value. If the project manager believes that this might not be the case, the system suggests that the next most likely scenario is that the brief is poor, followed by a tight schedule. The project manager can use the associated probabilities to provide guidance as to the relative likelihood of these scenarios. In this case, it can be noted that the poor brief is more than twice as likely as the tight schedule scenario. Therefore, if the project manager suspects that the project does have problems, the brief in this case would be the most likely scenario.

5.2 Problem Scenario

The second scenario is one where the construction process has more iterations, and therefore takes longer to pass the first gateway. In this scenario it is observed that the process passes the first gateway after 26 hops, i.e. that $\lambda = 26$. Again, expanding on Table 5, the ranked order can be read (1 Tight Schedule, 2 Poor Brief, etc.) and Table 7 provides this ranking with the associated conditional probabilities.

From Table 7 it can be seen that the top ranked scenario is that the schedule is too tight. However, it is worth noting that the second most likely scenario, a poor brief, has only a slightly lower probability of occurring (the difference in probabilities is ca. 0.001). With this additional information regarding the closeness of scenario probabilities, a project manager should investigate both scenarios. The third ranked scenario, Complex Project, is sufficiently distant that a project manager need only investigate this should the top two scenarios prove not to be the case.

Table 7: Ranked list of predicted scenarios for the case $\lambda = 26$ and associated conditional probabilities (to 4 d.p.).

Rank	Scenario (i)	$P(S_i \mid \lambda = 26)$
1	Tight Schedule	0.3261
2	Poor Brief	0.3260
3	Complex Project	0.1669
4	Small Budget	0.1554
5	Planning	0.0246
6	Nominal	0.0011

6 System Benchmarking

The Bayesian project diagnosis system uses estimated model parameters. The parameters are estimated from observed simulation runs. To benchmark (or assess) the project diagnosis system it is necessary to measure how well the system is able to predict a scenario. A simple yet effective method for benchmarking the system is to consider the observed freqencies (and ranking of these frequencies) of all the scenarios for the same range of λ values. The ranking from the empirical data used to estimate the model parameters is then compared to the same ranking generated from the model generated posterior probabilities. This is a well used benchmarking methodology, and has been used by many others (Anderson et al., 2009; Weidl et al., 2005; Fan and Yu, 2004).

The Bayesian project diagnosis system is used by the project manager considering the probabilities of various scenarios being played out. The probabilities are considered first in rank order, with further attention when two adjacently ranked scenarios have little difference between the probabilities. Therefore, an intuitive benchmark for the Bayesian diagnosis approach is to compare the Bayesian model probability estimates and the observed frequencies for a range of λ values. The Bayesian model based scenario ranking is given in Table 5 and the observed frequencies are given in Table 9. From these tables, the difference in rank is computed for each λ and is denoted d_λ. For example, in the top line of Table 10, under the Planners column the value 3 is computed by taking the difference between the same cell from Tables 5 (value=5) and Table 9 (value=2). These differences are then used to computed the Spearman rank correlation score. Where there are a total of n rankings to consider, the rank correlation is computed by (Siegel and Castellan, 1988):

$$\rho = 1 - \frac{6 \sum d_\lambda^2}{n^2(n-1)} \tag{5}$$

where $\rho = 1$ suggests total correlation. From Table 10, it can be seen that all Spearman scores are positive, with the majority greater than 0.5. This suggests that the model based ranking correlates well against the actual data that was used to parametrise the Bayesian model.

7 Discussion

The Bayesian project diagnosis support system assumes that the underlying distributions for the time taken to arrive at the gateway for each scenario can be represented by either a Poisson or Normal distribution. The simulation process is used to estimate the parameters of those models. For most scenarios, the χ^2 test suggested that this assumption was reasonable, as determined by sufficiently low χ^2 values (Table 3). However, for both the Difficult Planner and Poor Brief, the χ^2 test statistic for both distibution models was very high (Difficult Planners: $\chi^2_P = 6.13 \times 10^5$ and $\chi^2_N = 384$; Poor Brief: $\chi^2_P = 5.10 \times 10^8$ and $\chi^2_N = 12100$). This is not too critical for the Difficult planner scenario, as this occurs relatively rarely. However, for the Poor Brief, which is

Table 8: Observed frequencies for all scenarios for $8 \leq \lambda \leq 32$.

λ	Nominal	Complex	Sm. Budget	Diff. Planners	Poor Brief	Tight Sch.
8	0.44576	0.04558	0.05378	0.20693	0.11304	0.13491
9	0.38585	0.05662	0.06338	0.21169	0.13908	0.14338
10	0.36176	0.06469	0.08098	0.21562	0.13416	0.14279
11	0.33413	0.08065	0.09121	0.21123	0.14594	0.13682
12	0.27597	0.08539	0.12412	0.18662	0.17518	0.15273
13	0.22487	0.10519	0.12155	0.21459	0.18420	0.14960
14	0.18530	0.12353	0.13987	0.19806	0.19908	0.15416
15	0.15735	0.13158	0.15680	0.18969	0.20724	0.15735
16	0.10668	0.16861	0.19191	0.16738	0.19436	0.17106
17	0.08668	0.17141	0.18176	0.17853	0.19858	0.18305
18	0.06471	0.19954	0.21341	0.15023	0.21957	0.15254
19	0.06627	0.22855	0.20391	0.13594	0.19796	0.16737
20	0.04946	0.21860	0.21563	0.14441	0.19387	0.17804
21	0.03838	0.22614	0.22407	0.13382	0.19710	0.18050
22	0.02381	0.25063	0.23434	0.11905	0.18546	0.18672
23	0.01788	0.27923	0.22421	0.11692	0.17882	0.18294
24	0.01327	0.26534	0.25871	0.10779	0.14760	0.20730
25	0.00871	0.30836	0.28049	0.11672	0.13763	0.14808
26	0.00849	0.28238	0.26327	0.09766	0.16773	0.18047
27	0.00721	0.28125	0.24760	0.11058	0.16587	0.18750
28	0.00509	0.37150	0.24427	0.07888	0.14758	0.15267
29	0.00667	0.36667	0.24333	0.10667	0.13667	0.14000
30	0.00337	0.33333	0.29293	0.07407	0.12121	0.17508
31	0.00000	0.41129	0.26210	0.06048	0.08468	0.18145
32	0.00000	0.31416	0.28761	0.07080	0.11504	0.21239

Table 9: Scenario ranking from observations for $8 \leq \lambda \leq 32$.

λ	Nominal	Complex	Sm. Budget	Diff. Planners	Poor Brief	Tight Sch.
8	1	6	5	2	4	3
9	1	6	5	2	4	3
10	1	6	5	2	4	3
11	1	6	5	2	3	4
12	1	6	5	2	3	4
13	1	6	5	2	3	4
14	3	6	5	2	1	4
15	3	6	5	2	1	3
16	6	4	2	5	1	3
17	6	5	3	4	1	2
18	6	3	2	5	1	4
19	6	1	2	5	3	4
20	6	1	2	5	3	4
21	6	1	2	5	3	4
22	6	1	2	5	4	3
23	6	1	2	5	4	3
24	6	1	2	5	4	3
25	6	1	2	5	4	3
26	6	1	2	5	4	3
27	6	1	2	5	4	3
28	6	1	2	5	4	3
29	6	1	2	5	4	3
30	6	1	2	5	4	3
31	6	1	2	5	4	3
32	6	1	2	5	4	3

Table 10: Rank difference and Spearman rank correlation statistic for $8 \leq \lambda \leq 32$.

λ	Nom	Complex	Budget	Planners	Brief	Sched	Spearman
8	0	0	-1	3	-2	0	0.60
9	0	0	0	2	-2	0	0.77
10	0	0	0	2	-2	0	0.77
11	0	0	0	2	-1	-1	0.83
12	0	0	0	2	-1	-1	0.83
13	1	0	0	2	-2	-1	0.71
14	-1	0	-1	3	0	-1	0.66
15	-1	-1	-1	4	0	0	0.46
16	-3	1	2	1	0	-1	0.54
17	-3	0	1	2	0	0	0.60
18	-1	1	1	1	0	-2	0.77
19	0	2	2	0	-2	-2	0.54
20	0	2	2	0	-2	-2	0.54
21	0	2	2	0	-2	-2	0.54
22	0	2	2	0	-3	-1	0.49
23	0	2	2	0	-3	-1	0.49
24	0	2	2	0	-3	-1	0.49
25	0	2	2	0	-3	-1	0.49
26	0	2	2	0	-2	-2	0.54
27	0	2	2	0	-2	-2	0.54
28	0	2	2	0	-2	-2	0.54
29	0	2	2	0	-2	-2	0.54
30	0	1	2	0	-1	-2	0.71
31	0	1	1	0	0	-2	0.83
32	0	1	1	0	0	-2	0.83

the most common scenario, this potentially poses a problem. From Table 5 it can be seen that the Poor Brief is the top rated scenario for 52% (13 of 25 cases) of the λ range ($8 \leq \lambda \leq 32$).

Based on the rank correlation (as presented in Section 6 and in Table 10), the Bayesian project diagnosis system performs well. The benchmarking illustrated that there were relatively few cases where there was a large discrepancy between the ranking of the observed frequencies of the scenarios versus the model predicted posterior probabilities. For most observed λ values in Table 10, the Spearman correlation is greater than 0.5. Looking in greater detail at Table 10, this suggests that more attention is particularly warranted on the Poor Brief scenario. The diagnosis system almost always ranks this scenario higher than it actually occurs. Further analysis is possible through the comparison of Tables 4 (model generated posterior probabilities) and 8 (observed frequencies). From these it can be seen that the Poor Brief scenario is consistently overestimated, as well as the Tight Schedule. On the other hand the Difficult Planners scenario is underestimated throughout the range and Complex Design and Small Budget are underestimated mid-range. By considering Equation 1, this suggests that the prior probabilities should be revisited, lowering $P(S_{\mathrm{PB}})$, the prior probability of a Poor Brief and raising $P(S_{\mathrm{DP}})$, the prior probability of encountering difficult planners.

For comparison, Weidl et al. (2005) and Anderson et al. (2009) are both methodologically highly similar to this paper. Both these papers use Bayesian methods for estimating the impact of various events on the processes they are monitoring. Further, both papers evaluate their estimation power through simulation. Weidl et al. (2005) report for their root cause identification algorithm, they are able to achieve correct classification of at least 84%. This compares to the results from this paper where a Spearman correlation of between 0.5 and 0.8 was reported from the simulation experiment comparing the actual event occurring and the diagnosed (estimated) event using only the single observation of time elapsed.

Anderson et al. (2009) seek to estimate the process execution duration, given certain observed disturbances. This is equivalent to the reverse problem described in this paper: Anderson et al. observe an event and estimates the completion time (equivalent to estimating λ), while this paper seeks to estimate the disturbance given λ. It must be noted that the nature of the 'disturbance' is different: Anderson et al. (2009) has clear disturbances (e.g., labour strike, delayed material; delivery), whereas this project the disturbances are less clear to identify that they are occurring (e.g., poor brief, over complex project). The results from Anderson et al. are less straightforward to compare; however, they provide favourable comparison between the time estimates of a set of planned projects and the simulated estimates for these projects.

8 Conclusion

This study has shown that by using a Bayesian approach, it is feasible to diagnose the scenario that a process is experiencing using no more than the total time elapsed. Using this information, a project manager is able to take pre-emptive action to mitigate the impacts that are likely due to that scenario. This has been demonstrated using a mathematical simulation model of the construction design process. By using no more that the time taken to pass the first gateway review node, the Bayesian diagnosis method performs very well at identifying the most likely potential difficult scenarios. This compares very favourably with other similar diagnosis and estimation methods, with the benefit of only using one objective observation as opposed to a number of more subjective observations (e.g. 'New Technology' and 'Specification Discontent' from Lee et al. (2009)).

This project diagnosis would be of greatest use for novice project managers. These are the managers who due to less experience are most likely to need some direction to likely causes of difficulty with a project. More senior project managers would be expected in effect have a tacit diagnosis process, built up from many years' worth of experience.

There remain challenges with this work. The key challenge lies with the parameterising of the underlying conditional probability distributions. In this study this was acheived by modelling the process as a quasi-Markov chain, and then using a Monte Carlo approach to generate a sample distribution that the models could be fitted against. Within this approach the key challenge lies within the ability to suitably estimate the transition probabilities. These probabilities will be different for each construction company and for each type of project. The probabilities for this study were estimated through a combination of literature survey and discussions with practising construction project managers.

A drawback of the approach taken is that estimates of which scenario the project lies in are only available once the first gateway has been passed. This might well be too late for any mitigating actions to have significant impact. Solutions to this drawback could include observing different types of signals or to use time taken to other nodes. The first approach, identifying other signals, would require further work on the nature of the scenarios with a focus on characterising the scenarios and thereby identifying the observable signals. The second approach would be to apply a similar methodology as presented in this paper, but extending it to all nodes in the process. With both these approaches, the Bayesian method presented here can still be applied.

Overall, the Bayesian approach provides promising results. The key aspect is that relatively simple and subtle signals, such as the time taken to pass the first gateway review, can be used to estimate the global conditions in which the project finds itself. This study shows that there is potential for considering incorporating other signals to achieve better estimates of the scenario that a project is operating within. Further, although beyond the scope of this work, there is a need to develop suitable mitigating actions that would provide the means for recovering a project that is suffering from being in a hindering scenario. Ultimately, this diagnosis system provides the basis for an intelligent decision support system based on sound Bayesian methodology.

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A Transition Probabilities

This appendix contains the transition probabilities for the six different scenarios used in the simulation runs. The tables are laid out so that the originating nodes are shown on the left hand column. Therefore, each row represents the transition probabilities to the associated node listed in the top row. For compactness, the contents of each cell are in percentages. Blank cells represent that there is no connecting arc between the two nodes. This is to distinguish where there is an arc, but the probability of following this arc is zero, as is the case in say the Nominal scenario moving from state B1 to D. To further illustrate how to interpret the table, consider the first (Nominal) scenario: When the simulation is in Node F there is a 15% chance of progressing to Node D, a 30% chance of remaining in Node F, a 54% chance of progressing to Node GR1, and a 1% chance of Failure.

The process simulation is based on a Markov chain. The pure Markov chain is a memoryless construct: the transition to the next node is determined only by the node that the process is currently in. In the pure Markov chain history has no effect. In the construction process this is not the case. Tasks can be completed with degrees of success and the process can move on to the next tasks (state) even if a previous task has not been successfully completed. A rationale for this is that the project manager might not be aware or able to determine the task's success. To accommodate for this requirement, some of the states have been modified to have sub-states. For this simulation these are the first three states (A, B, and C). These sub-states are:

A: Project inception and definition

- A1 node A has not yet been completed (or has been done poorly);
- A2 node A has been successfully completed.

B: Identify site

- B1 node B activity fails to complete;
- B2 node B activity is successful, may move to C;
- B3 nodes B and C have been completed, can progress to D.

C: Outline project objectives

- C1 node C activity fails to complete;
- C2 node C activity is successful, may move to B;
- C3 nodes B and C have been completed, can progress to D.

A.1 Nominal

The Nominal scenario represents the case where the construction project proceeds well with no problems causing additional delay. There does remain a probability for the project to have to iterate, although in this scenario it will be relatively low.

	A	B	C	D	E	F	GR1	G	Fail
A1	30	35	35						
A2	15	42.5	42.5						
B1	20	10	70	0					
B2	5	10	85	0					
B3	1	6	8	85					
C1	20	70	10	0					
C2	5	85	10	0					
C3	1	8	6	85					
D		10	10		80				
E					20	80			
F				15		30	54		1
GR1	5							94	1

A.2 Complex

The Complex scenario represents the case where the proposed design is overly complex for the design specification needs. Issues that might arise in this scenario are that time management becomes more challenging, underground issues might arise due to complexity of design, etc. The affected nodes are C, D and F. These all now have a higher probability of transitioning back into an 'earlier' state.

	A	B	C	D	E	F	GR1	G	Fail
A1	30	35	35						
A2	15	42.5	42.5						
B1	20	10	70	0					
B2	5	10	85	0					
B3	1	6	8	85					
C1	37.5	35	27.5	0					
C2	50	27.5	22.5	0					
C3	12.7	19.7	17.4	50					
D		30	30		40				
E					20	80			
F				28.5		43.5	27		1
GR1	5							94	1

A.3 Small Budget

The Small Budget scenario represents the case where either the budget was set too low, or where suppliers have had problems and therefore that the expected costs have significantly risen. The affected nodes are C and D.

	A	B	C	D	E	F	GR1	G	Fail
A1	30	35	35						
A2	15	42.5	42.5						
B1	20	10	70	0					
B2	5	10	85	0					
B3	1	6	8	85					
C1	37.5	35	27.5	0					
C2	22.5	50	27.5	0					
C3	12.7	19.7	17.4	50					
D		35	35		30				
E					20	80			
F				15		30	54		1
GR1	5							94	1

A.4 Difficult Planners

The Difficult Planners scenario represents the case where regulating bodies place challenges on the progress of the project, for example where regulations are made stricter while the project is underway. The only node affected here is Node F.

	A	B	C	D	E	F	GR1	G	Fail
A1	30	35	35						
A2	15	42.5	42.5						
B1	20	10	70	0					
B2	5	10	85	0					
B3	1	6	8	85					
C1	20	70	10	0					
C2	5	85	10	0					
C3	1	8	6	85					
D		10	10		80				
E					20	80			
F				28.5		43.5	27		1
GR1	5							94	1

A.5 Poor Brief

The Poor Brief scenario represents the combination of either the initial specification for the construction project being poorly expressed or the client demanding a late change in the brief. This case affects only Node C (all sub-states).

	A	B	C	D	E	F	GR1	G	Fail
A1	30	35	35						
A2	15	42.5	42.5						
B1	20	10	70	0					
B2	5	10	85	0					
B3	1	6	8	85					
C1	42.5	25	32.5	0					
C2	27.5	40	32.5	0					
C3	16	23	21	40					
D		10	10		80				
E					20	80			
F				15		30	54		1
GR1	5							94	1

A.6 Tight Schedule

The Tight Schedule scenario represents the case where unrealistic time demands have been placed on the construction project. This can, for example, lead to mistakes being made due to rushed work. This case affects only Node F.

	A	B	C	D	E	F	GR1	G	Fail
A1	30	35	35						
A2	15	42.5	42.5						
B1	20	10	70	0					
B2	5	10	85	0					
B3	1	6	8	85					
C1	20	70	10	0					
C2	5	85	10	0					
C3	1	8	6	85					
D		10	10		80				
E					20	80			
F				33.5		48.5	17		1
GR1	5							94	1